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Covariance Risk and the Ripple Effect in the UK Regional Housing Market

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Abstract: This study combines two increasingly popular areas of the housing literature, by incorporating a measure of the ripple effect into a model of house price volatility. Using UK data for the English regions and Wales from 1995 to 2016, a multivariate GARCH model is initially used to produce time-varying covariances between house prices in London and other regions. These covariances are then incorporated into an EGARCH model of house price volatility showing that this covariance term is highly significant and positively signed in all regions, such that an increase in the covariance with London has a positive effect on a region's house prices. However the GARCH term in the mean equation produces a negative risk/return relationship across regional housing markets, although it is not robust to different specifications. This suggests that in the UK, when treating regional housing market risk, policies need to include the relationship of the region's house prices with those of London. Similar considerations could also apply in other countries exhibiting ripple effects in their housing markets.

Keywords: Covariance risk; Ripple effect; EGARCH; Housing

JEL Classification: R30, R11, G11

1. Introduction

The aim of this study is to analyse housing risk in conjunction with the ripple effect of regional house prices by introducing a covariance risk term into the standard risk model. Based on the Inter-temporal Capital Asset Pricing Model (ICAPM) of Merton (1973), we investigate the UK housing market by explicitly incorporating a covariance term between London house prices and other regional house prices into a conventional model of house price volatility. This term is intended to capture the effect of investors' desire to hedge against potential losses in their housing investment opportunities. While the importance of hedging in housing risk is empirically demonstrated by Han (2013) from a trading up perspective, the inclusion of the covariance term can be more specifically justified for the housing market in our study through the widely reported 'ripple effect' whereby changes in house prices in London are observed to ripple out to other regions across the UK.

The prominent role played by the housing sector during the financial crisis of 2008 (Duca *et al*., 2010) confirms that excessive volatility in the housing market can produce detrimental effects on the wider economy, through negative equity and mortgage foreclosure facilitating falls in aggregate consumption and output. Additionally, Case *et al*. (2005) find that the housing market has been an important wealth effect with respect to the wider economy, particularly through its influence on consumption. As a result of this, central banks across the world have developed specific policies to prevent a repeat of the crisis, adopting a more systemic approach to the regulation of financial institutions termed macro-prudential policy. Given that policies relating to the housing market are viewed as an integral part of the approach, with particular regard to the monitoring of house price to loan ratios, the existence of ripple effects needs to be explicitly incorporated into models of house price risk.

Following the literature review, the next section details our ICAPM based model and estimation procedures. The dataset is then explained and the results presented and assessed, with the concluding section indicating some policy implications.

2. Literature Review

Following Case and Shiller's (1989) seminal study of the efficiency and predictability of the housing market in terms of its similarities to more conventional asset markets, there has been accumulating literature relating to the asset properties of housing with particular regard to risk. Most of the extant studies on housing risk, which partly pre-date the 2008 financial crisis, have concentrated on measuring the risk in housing by testing for and then modelling any volatility clustering in house prices, usually with an Autoregressive Conditional Heteroskedastistic (ARCH) type of model. While early studies such as Drake's (1993) UK based study found little evidence of volatility clustering using the standard test for ARCH effects, Dolde and Tirtiroglue's (1997) use of the Generalised ARCH (GARCH) model showed evidence of a link between house price volatility and the regional economy in the US. More recent studies such as Miles (2008) and Karaglou *et al.* (2013) have found evidence of clustering in the US housing market, and this has been increasingly noted for other countries, especially the UK (Tsai *et al*. 2010, Miles, 2011). Various GARCH based models have been used to model the associated risk, including GARCH-in-mean models in order to investigate the risk/return relationship and any asymmetry in the volatility. One of the main findings from the literature has been that, although there is evidence of a significant relationship between house price returns/excess returns and risk, the sign is often negative and tends to vary across studies and in particular across national regions.

Amongst the variety of approaches to modelling volatility clustering the Exponential GARCH (EGARCH) model is particularly popular, as it incorporates asymmetry into the model, such that negative shocks have a different effect on volatility to positive shocks[1]. For example Morley and Thomas (2016) found evidence of significant risk/return relationships and asymmetry in the UK, although the sign on the risk/return relationship varied across the regions. Using Canadian house price data, Lin and Fuerst (2014) have also used the EGARCH approach to model the relationship, again finding significant risk/return relationships but with the same variation in signs across regions encountered by other studies.

The literature analysing the ripple effect or convergence in house prices within countries also extends back to before the financial crisis. As Meen (1999) notes, evidence of the ripple effect

[1] There is also an extensive literature on the EGARCH-in-mean model with equity markets, such as Scruggs (1998), and even with equity markets the relationship between risk and return can be negative. As with the housing literature it tends to differ across markets and studies.

implies a long-run stationarity in the ratio between regional house prices and aggregate countrywide house prices. Much of the evidence on the existence of the ripple effect stems from tests for stationarity on the house price ratio, along with a literature which has used cross-correlation analysis and Granger-causality tests, such as Cook (2003). Although much of the UK based literature finds evidence of the regional ripple effect the results have failed to reach a complete consensus on its existence. While Meen's (1999) study found little evidence of the ripple effect in the UK, an accumulation of other studies such as Cook (2003, 2012), Holmes and Grimes (2008), and Hudson *et al.* (2018) have found significant evidence of its existence, usually originating from London and declining the further the region's distance away. Supporting evidence for the regional ripple effect has also been provided by Holmes *et al.* (2011) and Payne (2012) for the US, albeit with the latter identifying regional centres or multiple sources rather than a single source of the ripple.

Against this background the aim of this study is to combine the two literature strands to explain some of the anomalies found in previous studies of volatility, with particular emphasis regarding the extent to which covariance risks impact on the housing market, and offering an alternative explanation to the nature of the ripple effect.

The theoretical explanation for the existence of the ripple effect covers a number of factors, but has mainly concentrated on migration between regions, which produces a spatial arbitrage process between the regional housing markets (Meen, 1999). This also formed the basis of other approaches to explaining the ripple effect, as in Jones and Leishman (2006), although they also emphasise that other factors could cause the effect, such as infrastructure links. It is usually assumed the effect of one region's house prices on another is positive. Although the ripple effect has so far tended not to be linked specifically with investment opportunities, Han (2008) has analysed housing markets and the relevance of risk hedging mechanisms. As Han (2013) notes, there is an incentive for households to hedge housing risks and this increases as they become more likely to trade up in the housing market within positively correlated markets, and this phenomenon could be a potential explanation for the ripple effect from a financial perspective. With specific regard to the UK situation, a more particular reason for the ripple effect could be the need for investors in London property to hedge against adverse movements in the London market, by also investing outside London and vice versa, hence the importance of the relationship between UK regional house prices and London prices when considering risk and return across the UK regional housing market.

3. Model and Methodology

The approach used here is based on the ICAPM of Merton (1973) as adopted by Scruggs and Glabadanidis (2003) to model the US stock market premium, with the house price premium replacing stock price premium. In order to reflect the importance of the ripple effect in house prices, a time-varying co-variance-in-mean term, rather than more usual correlations, have been incorporated into the EGARCH model, where this term measures the covariance between central London house prices and the specific regional price.

The Merton (1973) model assumes a risk averse agent with the following utility of wealth function:

$$J(W(t), F(t), t) \qquad (1)$$

where $W(t)$ is wealth and $F(t)$ is a variable that measures the state of investment opportunities in the economy. The equilibrium expected market risk premium takes the following form:

$$E_{t-1}(r_{Mt}) = \left[\frac{-J_{WW}W}{J_W}\right]\sigma^2_{Mt} + \left[\frac{-J_{WF}}{J_W}\right]\sigma_{MFt} \qquad (2)$$

where $E_{t-1}[\cdot]$ represents the expectations operator, and σ^2_{Mt} and σ_{MFt} are the market variance and covariance with state variable F respectively; all conditional on information available at time *t-1* and where subscripts on J are the partial derivatives. The first term in parentheses is the Arrow-Pratt coefficient of relative risk aversion, implying that $J_W > 0$ and $J_{WW} < 0$. If $J_{WF} \neq 0$, then the covariance with the state variable will also affect the housing excess return or risk premium, although the relationship between this term and the dependent variable is complex. If $J_{WF} > 0$ and $\sigma_{\mathrm{MF,t}} < 0$ or if $J_{WF} < 0$ and $\sigma_{WF,t} > 0$ then the investors will demand a higher risk premium on the market portfolio, which pays off in situations where the marginal utility of wealth is small. However in the event that the inequality in the previous case is the same for both terms, investors would demand a lower risk premium. If the model of risk and excess returns is estimated without this covariance term Scruggs (1998) shows that the estimates will be biased. Scruggs and Glabadanidis (2003) and Chan *et al.* (1992) both find that there is a positive relationship between the covariance term and equity excess returns, whilst the conditional variance is either negative or not significant. Although both these studies were based on US equity market excess returns and the state variables used are different to the one used here, we too expect the covariance term to be positively signed.

As suggested by Scruggs (1998), additional assumptions are required to ensure the model becomes empirically useable. These include the assumption that the conditional second moments are time-varying and also follow the EGARCH type of process. Based on this it is possible to produce conditional versions of the traditional CAPM, if we make a number of further assumptions such as the investment opportunity set being static. The model implies that there should be a simple proportional relationship between the housing market excess return, as measured by the difference between the monthly return on housing and the monthly risk free interest rate, and the conditional housing market variance, in a similar way to that hypothesised and subsequently found by Scruggs (1998) in the US stock market. Potential differences in this relationship could be due to varying perceptions to risk and different degrees of risk aversion across regions and property types. However, as noted by Veronesi (2000), although the conventional expectation is of a positive risk and return relationship with respect to stock returns, the nature of this relationship can be ambiguous as a result of changing levels of investor uncertainty over time regarding an economy's true growth rate, with the relationship even becoming negative at high levels of uncertainty. Following this the above model can be estimated with the standard EGARCH(1,1)-M model of Nelson (1991), which has a number of advantages over the alternative models, such as the GARCH(1,1) model, as it is able to overcome the non-negativity constraint and also incorporates asymmetry into the model.

More specifically, and given the particular focus of our study, the EGARCH approach is employed rather than a multivariate GARCH model as it is assumed the covariance term reflects the existence of the ripple effect, with London as its origin, and that the shock to London house prices is exogenous; for instance as a result of demand facilitated by animal spirits. Although most studies identify London as the origin of the UK's housing shocks, as Holmes and Grimes (2008) suggest, there is little research on the specific determinants of the initial shock. However, a further potential source of such shocks could be through overseas investment in the London real estate market, which has become increasingly common in recent years. Liao *et al.* (2015) found evidence of such overseas shocks to the central region in Singapore, which subsequently ripple out to the outer regions despite very few overseas purchases in the outer regions. In this case we are assuming London's housing market is not affected by the regions, and the mean of the model, which is similar to Scruggs and Glabadanidis (2003) has the following form:

$$\Delta \ln hp_t = \alpha_0 + \alpha_1 \sigma_t^2 + \alpha_2 \sigma_{RiL} + u_t \tag{3}$$

where σ_t^2 is the conditional volatility and σ_{RiL} is the covariance between region *Ri* and the state variable which in this case is London's *(L)* house price excess return, as suggested by Holmes and Grimes (2008) among others. The conditional volatility[2] follows the EGARCH specification:

$$\ln(\sigma_t^2) = \lambda + \phi \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \beta \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \tag{4}$$

In equation (4), if $\gamma < 0$ as expected with asset returns, it suggests a leverage effect whereby a fall in house prices leads to increased volatility and riskiness in the housing market as a result of the rise in the leverage ratio. Given the particular dynamics of regional housing markets in the UK, which differs from those in international stock markets and given the presence of the ripple effect stemming from London, we use London house prices as the state variable. In the ICAPM, state variables reflect the wish by investors to hedge against potential losses in available investment opportunity sets[3], and if the change in regional house prices differs to London's this makes it a potential hedge. In this case the correlation between region *i* and London's excess returns is assumed to be time varying, as many studies argue the importance of accounting for the inter-temporal nature of market risk premiums (Evans, 1994). In addition, in equation (3) the coefficient α_2 should have the opposite sign to J_{WF}. The time-varying covariance between regional and London house price excess returns is generated using a dynamic conditional correlation (DCC) approach, originally devised by Engle (2002), which is also used to provide the standard deviations for the respective house price returns. In addition, the respective covariances (σ_{RL}) can be formed from the time-varying correlations between region *Ri* and London (*L*) (ρ_{RiL}) and standard deviations of the individual series (σ_{Ri} for region i and σ_L for London) as below:

$$\sigma_{RL} = \rho_{RiL}\, \sigma_{Ri}\, \sigma_L \tag{5}$$

The covariances between regional house prices and London house prices are generated from a bi-variate Dynamic Conditional Correlation (DCC) model, with the approach having the advantage over other multivariate models in that there are a reduced number of parameters to estimate. In addition, unlike the constant conditional correlation model, it produces time-varying correlations which can be used to produce the time varying covariances. If we denote $\mathbf{r}_t$ as an $m \times 1$ vector of house price risk premiums, the conditional mean and variance would be:

[2] There are many other methods for estimating risk in the literature, such as the standard deviation of the difference between actual and expected transaction price (Peng and Thibodeau, 2017). However as this approach to modelling risk and return is based on Scruggs (1998) we have followed his approach and also used a GARCH based model.

[3] Scruggs (1998) uses the long-term government bond interest rate as the state variable in the ICAPM based model of equity markets, finding that the covariance between market risk premium and the bond rate is negatively and significantly related to the market risk premium.

$$\mu_{t-1} = E(r_t \mid \Omega_{t-1})$$
$$\Sigma_{t-1} = Cov(r_t \mid \Omega_{t-1})$$

where it is assumed that Σ_{t-1} is non-singular and Ω_{t-1} is the information set at t-1. The conditional covariance can be expressed in terms of the following decomposition:

$$\Sigma_{t-1} = D_{t-1} R_{t-1} D_{t-1} \tag{6}$$

where D_{t-1} is an $m \times m$ diagonal matrix with the elements being the conditional volatilities of house price risk premiums. R_{t-1} is a symmetric $m \times m$ matrix of pair-wise conditional correlations. For the *i*th asset premium the conditional volatility is:

$$\sigma^2_{i,t-1} = Var(r_{it} \mid \Omega_{t-1}) \tag{7}$$

The conditional correlations between the *i*th and *j*th house price risk premium are:

$$\rho_{ij,t-1} = \rho_{ji,t-1} \frac{Cov(r_{it}, r_{jt} \mid \Omega_{t-1})}{\sigma_{i,t-1}\sigma_{j,t-1}} \tag{8}$$

We can then estimate the following GARCH(1,1) model for $\sigma^2_{i,t-1}$:

$$\sigma^2_{i,t-1} = \bar{\sigma}^2_i (1 - \lambda_{1i} - \lambda_{2i}) + \lambda_{1i}\sigma^2_{i,t-2} + \lambda_{2i} r^2_{i,t-1} \tag{9}$$

For the conditional correlations, the (*I*, *j*)th correlation is:

$$\bar{\rho}_{ij,t-1}(\phi) = \frac{q_{ij,t-1}}{\sqrt{q_{ii,t-1} q_{jj,t-1}}} \tag{10}$$

where $q_{ij,t-1}$ is specified as :

$$q_{ij,t-1} = \bar{\rho}_{ij}(1 - \phi_1 - \phi_2) + \phi_1 q_{ij,t-2} + \phi_2 \tilde{r}_{i,t-1} \tilde{r}_{j,t-1} \tag{11}$$

and $\bar{\rho}_{ij}$ is the (*i*, *j*)th unconditional correlation. The $\tilde{r}_{i,t-1}$ are the standardised premiums and $\phi_1 + \phi_2 < 1$. The DCC model is estimated by Maximum Likelihood and we assume a multivariate Gaussian distribution[4]. The estimation and evaluation of the DCC model occurs in a recursive way, such that the time period is sub-divided into three samples. The first set of observations is used for the initialisation, the second sample for estimation and the latter for its evaluation.

4. Data and Results

The house price data are the average seasonally adjusted monthly house prices from the Acadametrics House Price Index[5], which is based on property price data collected by the UK Land Registry. Unlike many other house price indices this is compiled using data from cash purchases of houses as well as the more commonly used mortgage data. The data relates to the English regions, including London, together with Wales as a single region, for the period from January 1995, which

[4] See Pesaran and Pesaran (2009) for a full description of this version of the DCC model.

[5] We are grateful to LSL Property Services for the data used in this study (http://www.acadata.co.uk).

was the earliest date available, until May 2016. The return on housing is in excess return or risk premium form where the nominal monthly risk free rate is subtracted from the monthly nominal return on the house price index. The risk free rate is proxied by the interest rate on a three month Treasury Bill obtained from the Bank of England.

4.1 Covariance between London and UK regions

Table 1 contains the summary statistics for house price indices across the regions of England and Wales. It is clear that London has the highest prices and also the highest variation, reflecting the importance of the London market to the UK housing market. The South East has the second highest house prices, although its variability is no higher than other regions across the UK[6]. House prices decline the further away a region is from London, with the lowest prices being in the North East, where average prices are almost three times less than London values.

Table 1. Summary statistics

Region	Mean	Median	SD	CV
Lon (London)	323278.4	322291.6	132090.2	0.409
SE (South East)	226832.4	241510.7	72548.1	0.320
SW (South West)	182428	204446.7	58608.4	0.321
EA (East Anglia)	190070.9	206837.5	63051.2	0.332
EM (East Midlands)	134936.1	155639.9	42285	0.313
WM (West Midlands)	143353.6	162918.5	43413.9	0.303
Wales	123974.7	147662.7	40946.8	0.330
Yorks (Yorkshire)	125444.2	145961.5	41699.7	0.332
NW (North West)	125804.9	147734.1	40894.9	0.325
NE (North East)	112548.6	133058	36632.7	0.325

Notes: Data for raw regional house prices from 1997m1 to 2016m5. CV is the coefficient of variation.

Table 2 contains the unit root tests using the Phillips-Perron test and Kwiatkowski Phillips Schmidt Shin test, with the former having the null hypothesis of the series containing an unit root whilst the latter has the null hypothesis of stationarity. The results show that all series are stationary at the 1% level of significance and so can be used for estimation.

Table 2. Tests for stationarity

Region	Lon	SE	SW	EA	EM
PP	-8.317***	-7.157***	-6.515***	-7.378***	-6.580***
KPSS	0.109	0.133	0.366	0.240	0.354
Region	**WM**	**Wales**	**Yorks**	**NW**	**NE**
PP	-7.157***	-7.907***	-6.880***	-6.931***	-8.768***
KPSS	0.262	0.409	0.287	0.273	0.262

Notes: PP is the Philips-Perron test, and KPSS is the Kwiatkowski Phillips Schmidt Shin test. Asterisks *** indicate rejection of the null hypothesis at the 1% level of statistical significance.

6 These statistics relate to the raw house price data, but as the riskless rate of interest is very small during the data sample the results are similar to the housing market risk premium. The standard test for the ARCH effect was conducted on the regional housing risk premium data by regressing this variable on a constant then testing for ARCH(12) using the LM test, with the effects indicating significant ARCH effects in all regions.

In order to produce the time-varying correlations between the regions and London, the DCC model is used for each individual region alongside London. This is also used to produce the time-varying standard deviations of the region and London's house prices, which are then used to calculate the covariances. To allow for the presence of mean-reverting conditional correlations, the decay factors for the covariances are unrestricted. A rolling historical volatility was used with a window of 20 observations; the same number used for the initialisation of the estimation. Overall the covariances[7] are gently undulating until about 2008 when they increase in volatility - coinciding with the financial crisis and increasing risk in the housing market - before becoming more stable again after 2012. In the South East, South West and East Anglia regions there was an increase in covariance during the financial crisis that has subsequently fallen back, which has tended not to be the case in the regions further away from London.

4.2 Estimation results of DCC model

Table 3 presents the estimates for the parameters in the DCC specification for all the regions and the estimates are predominantly significant in all cases, with the sum of the lambdas being well below unity for all regions, suggesting the volatility is mean reverting[8].

Table 3. Multivariate GARCH results between regions and London

Region	$\lambda_1 reg$	$\lambda_1 Lon$	$\lambda_2 reg$	$\lambda_2 Lon$	δ_1	δ_2	LL
SE	0.295**	0.686***	0.354***	0.146**	-0.168	0.272***	1212.9
	(2.311)	(3.436)	(5.344)	(2.485)	(1.660)	(3.671)	
SW	0.254	0.862***	0.412***	0.091**	0.921***		1199.0
	(1.774)	(11.543)	(5.782)	(2.475)	(26.026)		
EA	0.328***	0.857***	0.363***	0.086	0.921***	-0.003	1218.2
	(2.754)	(6.204)	(4.922)	(1.537)	(16.901)	(0.125)	
EM	-0.177	0.593**	0.425***	0.206***	-0.125	0.430***	1196.0
	(0.910)	(2.507)	(4.200)	(3.159)	(1.908)	(6.441)	
WM	0.142	0.688***	0.370***	0.173***	-0.109	0.361***	1182.8
	(1.013)	(4.760)	(4.400)	(3.024)	(1.887)	(5.575)	
Wales	0.208	0.580***	0.359***	0.223***	-0.112***	0.407***	1182.3
	(1.112)	(3.163)	(4.017)	(3.603)	(2.729)	(5.731)	
Yorks	-0.027	0.614***	0.379***	0.205***	0.037	0.424***	1175.2
	(0.167)	(3.535)	(4.228)	(3.497)	(0.327)	(6.495)	
NW	0.092	0.761***	0.366***	0.159***	-0.079	0.410***	1186.0
	(0.566)	(7.090)	(4.553)	(2.937)	(0.692)	(6.148)	
NE	0.360	0.600***	0.232***	0.223***	0.129	0.350***	1131.9
	(1.368)	(3.605)	(2.996)	(3.657)	(0.656)	(5.214)	

Notes: See Tables 1 and 2. See DCC model for details on parameters. T-statistics are in parentheses below the estimated parameters.

Table 4 on the next page reports the estimates of the correlations and volatilities, with London shown to be the most volatile and East Anglia, the East Midlands and Wales being the least volatile, indicating that volatility generally tends to be less the further from London the region is, with the exception of the North East. A similar pattern is observed with the time-varying correlations, with

[7] The covariance graphs are available from the authors on request.

[8] In all cases the lambda which measures the decay for the variance was unrestricted, rather than being restricted to sum to unity, but for the South West (SW) the model failed to converge unless this restriction was applied. Microfit 5 was used to estimate the DCC model and overall convergence was obtained.

the South East having the highest correlation coefficient of 0.718, followed by East Anglia with 0.624. Both regions border London with the South East in particular containing a large number of commuters to London. The correlation coefficients fall as expected as distance increases up to the North East, which records a correlation coefficient of just 0.214; again appearing to support the London sourced 'ripple effect'.

Table 4. Unconditional correlations and volatilities

Region	SE	SW	EA	EM	WM	Wales	Yorks	NW	NE
Corr	0.718	0.593	0.624	0.312	0.394	0.330	0.363	0.344	0.214
σ^2Lon	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019
σ^2Reg	0.016	0.014	0.013	0.013	0.014	0.013	0.014	0.014	0.016

Notes: Corr is the unconditional correlation coefficients and the subsequent statistics refer to the volatility of London and the regions respectively.

Table 5 contains the results for the E-GARCH estimations, based on equations (3) and (4) including the use of Bollerslev-Wooldridge covariances and standard errors, as in Scruggs and Glabadanidis (2003), and the mean equation includes both the GARCH and covariance terms [9].

Table 5. EGARCH models for the individual regions

Region	Mean equation			Variance equation				$\bar{R}^2$
	Const	GARCH	Cov	λ	φ	γ	β	
SE	0.020***	-244.327***	1.477***	-4.225***	-0.005	-0.209***	0.527***	0.43
	(2.643)	(6.500)	(3.920)	(4.013)	(0.087)	(3.261)	(4.511)	
SW	-0.004	-196.721***	2.832***	-3.022***	-0.374***	-0.530***	0.658***	0.46
	(1.104)	(10.067)	(6.607)	(5.432)	(4.969)	(9.635)	(11.130)	
EA	0.008	-237.035***	2.566***	-3.070***	0.016	-0.215**	0.664***	0.37
	(0.825)	(3.823)	(4.331)	(4.117)	(0.153)	(2.257)	(8.118)	
EM	0.026***	-332.582***	0.746***	-3.691***	-0.071**	-0.201***	0.603***	0.49
	(6.746)	(14.744)	(4.174)	(5.204)	(2.238)	(7.380)	(7.964)	
WM	0.039***	-441.074***	0.916***	-3.921***	-0.013	-0.136***	0.575***	0.50
	(5.092)	(10.804)	(4.586)	(5.261)	(0.448)	(6.171)	(7.1004)	
Wales	0.042***	-428.565***	0.956***	-3.292***	-0.003	-0.098***	0.641***	0.43
	(3.150)	(6.698)	(6.335)	(3.396)	(0.120)	(3.641)	(6.115)	
Yorks	0.021***	-269.728***	0.318***	-4.012***	-0.049	-0.241***	0.566***	0.56
	(5.825)	(10.196)	(7.020)	(5.250)	(1.011)	(5.306)	(6.905)	
NW	0.033***	-375.947***	0.913***	-3.977***	-0.053	-0.162***	0.567***	0.49
	(4.979)	(10.978)	(4.667)	(5.107)	(1.540)	(5.933)	(6.800)	
NE	0.011	-90.556**	1.707***	-5.058***	-0.008	-0.332***	0.423***	0.36
	(1.915)	(2.373)	(7.509)	(4.318)	(0.116)	(3.284)	(3.166)	

Notes: See Table 3. Parameters as in equations (3) and (4). Z-statistics in parentheses. Coefficient covariances estimated with Bollerslev-Wooldridge QML sandwich and expected Hessian. $\bar{R}^2$ in the last column denotes adjusted R-squared.

[9] An alternative would be to use Huber-White robust standard errors. However this made little difference to the results. Also the addition of a number of AR terms was tried, but this caused a failure to converge in a number of regions so was not used here. In those regions where convergence was achieved the covariance term was significantly positive although the GARCH term in many cases was not significant.

In this Table, the GARCH term in all regions is significant at the 5% level, although it is negatively signed in all cases. In addition in all regions the correlation with the London covariance term is significant, mostly at the 1% level of significance. In the variance equation the results are relatively consistent across regions with particular regard to asymmetry, where the negative sign on this term suggests the leverage effect is present such that a fall in house prices increases volatility and therefore risk more than a rise in prices. The volatility persistence measures are also mostly significant, with the levels of persistence varying across regions. The regions closest to London tend to have the most persistent volatility, with the South West recording the highest with 67% of the volatility persisting one time period later.

These results suggest that there is a consistent negative relationship between risk and excess return in the UK housing market. Most studies of the UK housing market find considerable heterogeneity in terms of the impact of GARCH based volatility across the regions (Miles, 2011) and this tends to also be the case in other countries, such as Canada (Lin and Fuerst, 2014). Scruggs and Glabadinidis (2003) employ a similar approach to estimating the variance and covariance risk for the US equity market premium using an Asymmetric Dynamic Correlation (ADC) model. However, while finding some evidence of a negative relationship between the equity market risk premium and conditional variance and, in one specification, a positive sign and significance for the covariance term, Scruggs and Glabadinidis (2003) conclude that they find little evidence overall to support the model.

4.3 Robustness tests

The nature of the housing market has changed appreciably since the 2008 financial crisis in terms of its dynamics and the relationship between regions and the wider economy. In order to model any potential affects these changes may have had on house prices, a dummy variable (D) and an interaction variable between the dummy and the covariance between the region and London (D*Cov) has been introduced into the model. The dummy variable is zero until August 1998 and one thereafter to reflect the critical effect that the Lehman Brothers investment bank collapse had on the international financial system including the UK and its influence on the wider housing market[10] as many lenders found access to funding more limited following the failure of the short-term money markets.

This modification produces the following model where the EGARCH variance specification is the same as before:

$$\Delta \ln hp_t = \alpha_0 + \alpha_1 \sigma_t^2 + \alpha_2 \sigma_{RiL} + \alpha_3 D_t + \alpha_4 D_t * \sigma_{RiL} + u_t \qquad (12)$$

Table 6 contains the results for the mean equation (the results of the variance equation are not included as they differ very little to those in Table 4.). With respect to the co-variance terms, there is very little difference to the results from table 4, as the covariance term remains largely positive and significant, whilst the variance term is still mainly significant and negative, suggesting that accounting for the effects of the financial crisis has little effect on this covariance term. However in two regions, the South West and East Midlands the variance term becomes insignificant, suggesting this effect is not particularly robust.

[10] Although the financial crisis began in the UK with the collapse of the Northern Rock Bank in September 2007, the collapse of Lehman Brothers was used as the financial crisis starting point as it had wider implications on the international financial system and facilitated the collapse of other banks in the UK such as Bradford and Bingley. This in turn facilitated a decline in the UK housing market. We also tried using other dummy variables, such as one for the September 2007 crises, but these were not as significant and did not materially affect the results.

Table 6. EGARCH models for individual regions with crisis effect

Region	Const	GARCH	Cov	D	D*Cov	$\overline{R}^2$
SE	0.016	-236.692***	1.924***	-0.001	-0.443	0.44
	(1.838)	(4.839)	(4.593)	(0.156)	(0.834)	
SW	-0.014	118.642	1.134***	0.005	-1.334***	0.50
	(1.266)	(0.830)	(2.977)	(1.778)	(3.350)	
EA	0.003	-243.495**	3.737***	-0.009	-0.369	0.41
	(0.184)	(2.526)	(5.047)	(0.984)	(0.390)	
EM	0.001	-83.669	1.331***	0.003	-0.947***	0.52
	(0.310)	(1.332)	(7.332)	(1.694)	(3.813)	
WM	0.030***	-362.842***	1.363***	-0.001	-0.591	0.51
	(4.599)	(10.265)	(5.402)	(0.295)	(1.779)	
Wales	0.045***	-523.303***	1.564***	-0.000	-0.988***	0.47
	(2.911)	(5.852)	(8.309)	(0.159)	(3.850)	
Yorks	0.022***	-268.934***	0.339***	-0.004	-0.023	0.56
	(5.725)	(10.735)	(3.861)	(1.521)	(0.251)	
NW	0.030***	-384.475***	1.351***	-0.001	-0.683**	0.50
	(5.499)	(12.645)	(5.337)	(0.193)	(2.253)	
NE	0.003	-46.036***	2.465***	-0.001	-1.330***	0.35
	(1.311)	(2.914)	(11.508)	(0.312)	(4.148)	

Notes: See Tables 4 and 5. D is the dummy variable taking the value of 0 prior to 1998m9 and 1 thereafter. D*Cov is an interaction term between the covariance and dummy variable. Variance equation not reported as similar to previous table.

The extent to which the financial crisis affected house price dynamics varies across the regions, with regions furthest away from London generally exhibiting the most substantial effects. The dummy variable itself is not significant in any regions suggesting that the crisis itself has not affected house prices. In the regions closest to London, only in the South West was the interaction crisis dummy variable significant, in this case negatively signed. However the interaction variable is significant and negative in Wales, the East Midlands, the North West and North East. This suggests that the effect from London to these regions has been reduced since the crisis, suggesting London is less of a hedge than it was before the crisis. This could also be due to increasing flows of capital into London from abroad, such that London could also be a hedge for international housing markets, so driving it away from regional markets.

5. Conclusion

The results from this study suggest that the relationship between the UK housing market with respect to excess returns and volatility is relatively complex, with the main driver of returns being based on the relationship between a specific region's house prices and London house prices. As expected the regions surrounding London have a substantially larger correlation with London than do regions further away. In addition, in terms of the EGARCH specification, the relationship between risk and excess return observed in previous studies appears to be more consistent across regions, albeit with a negative sign. With the inclusion of the covariance term other aspects of previous study results also become more consistent, such as the significant asymmetric effect and persistence of shocks.

The study also shows the importance of hedging in the opportunity set of investments in the UK housing market, indicating a possible explanation for the ripple effect in regional housing markets, as previously noted by Han (2013). It also suggests that the covariance term which models the hedging effect is reasonably robust, although as in other studies the risk and excess returns relationship is less robust to alternative specifications of the model, with covariance risk shown to be more important than variance risk. There is also evidence that the 2008 financial crisis has had an effect on the covariance risk, with regions furthest away from London being increasingly less affected by changes in London prices post-crisis.

With regards to policy design the main implication of this study is that it is the ripple effect with regard to covariance risk that dominates house prices in the UK regions and when this effect is accounted for in a volatility model, the effects of risk on house prices are less robust. Given the substantial part played by the housing market in the financial crisis, it has become increasingly important for policy makers to understand the dynamics of the UK housing market. This is because the current use of macro-prudential policies by central banks to ensure the stability of the financial system involves the monitoring of lending to the housing market and changes in house prices along with their volatility. As the London housing market has recently experienced sharply rising house prices as a result of increased overseas investment, it appears to be particularly important to be able to understand and predict the implications of this to the wider housing sector outside London in order to ensure future stability in the housing market and the financial institutions that provide the finance for this market. Given the well-established presence of ripple effects in other countries, including the US, our results and their implications are potentially applicable for other housing markets to varying degrees of complexity.

References

[1] Case, K. and Shiller, R. (1989). “The efficiency of the market for single family homes”, *American Economic Review*, 79 (1): 125-137.

[2] Case, K., Quigley, J. and Shiller, R. (2005). “Comparing wealth effects: The stock market versus the housing market”, *Advances in Macroeconomics*, 5 (1): 1-34.

[3] Chan, K.C., Karoly, G.A. and Stultz, R.M. (1992). “Global financial markets and the risk premium on U.S. equity”, *Journal of Financial Economics*, 32 (2): 137-167.

[4] Cook, S. (2003). “The convergence of regional house prices in the UK”, *Urban Studies*, 40 (11): 2285-2294.

[5] Cook, S. (2012). “β-convergence and the cyclical dynamics of UK regional house prices”, *Urban Studies*, 49 (1): 203-218.

[6] Dolde, W. and Tirtiroglue, D. (1997). “Temporal and spatial information diffusion in real estate price changes and variances”, *Real Estate Economics*, 25 (4): 539-565.

[7] Drake, L. (1993). “Modelling UK house prices using cointegration: An application of the Johansen technique”, *Applied Economics*, 25 (9): 1225-1228.

[8] Duca, J., Muellbauer, J. and Murphy, A. (2010). “Housing markets and the financial crisis of 2007-2009: Lessons for the future”, *Journal of Financial Stability*, 6 (4): 203-217.

[9] Engle, R. (2002). “Dynamic Conditional Correlation – A simple class of multivariate GARCH models”, *Journal of Business and Economic Statistics*, 20 (3): 339-350.

[10] Evans, M. (1994). “Expected returns, time-varying risk and risk premia”, *Journal of Finance*, 49 (2): 655-679.

[11] Han, L. (2008). “Hedging house price risk in the presence of lumpy transaction costs”, *Journal of Urban Economics*, 64 (2): 270-287.

[12] Han, L. (2013). "Understanding the puzzling risk-return relationship for housing", *Review of Financial Studies*, 26 (4): 877-928.

[13] Holmes, M., and Grimes, A. (2008). "Is there long-run convergence among regional house prices in the UK?", *Urban Studies*, 45 (8): 1531–1544.

[14] Holmes, M., Otero, J. and Panagiotidis, T. (2011). "Investigating regional house price convergence in the United States: Evidence from a pair-wise approach", *Economic Modelling*, 28 (6): 2369-2376.

[15] Hudson, C., Hudson, J and Morley, B. (2018). "Differing house price linkages across UK regions: A multi-dimensional recursive ripple effect", *Urban Studies*, 55 (8): 1636-1654.

[16] Jones, C. and Leishman, C. (2006). "Spatial dynamics of the housing market: An interurban perspective", *Urban Studies*, 43 (7): 1041-1059.

[17] Karoglou, M., Morley, B. and Thomas, D. (2013). "Risk and structural instability in US house prices", *The Journal of Real Estate Finance and Economics*, 46 (3): 424-436.

[18] Liao, W-C., Zhao, D., Lim, L-K. and Wong, G. (2015). "Foreign liquidity to real estate market: Ripple effect and housing price dynamics", *Urban Studies*, 52 (1): 138-158.

[19] Lin, P-T. and Fuerst, F. (2014). "Volatility clustering, risk-return relationships and asymmetric adjustment in Canadian housing markets", *Journal of Real Estate Portfolio Management*, 20 (1): 37-46.

[20] Meen, G. (1999). "Regional house prices and the ripple effect: A new interpretation", *Housing Studies*, 14 (6): 733–753.

[21] Merton, R. (1973). "An intertemporal asset pricing model", *Econometrica*, 41 (5): 867-888.

[22] Miles, W. (2008). "Volatility clustering in US home prices", *Journal of Real Estate Research*, 30 (1): 73-80.

[23] Miles, W. (2011). "Clustering in UK home price volatility", *Journal of Housing Research*, 20 (1): 87-101.

[24] Morley, B. and Thomas, D. (2016). "An empirical analysis of UK house price risk variation by property type", *Review of Economics and Finance*, 6 (2): 45-56.

[25] Nelson, D. (1991). "Conditional heteroskedasticity in asset returns: A new approach", *Econometrica*, 59 (2): 347-370.

[26] Payne, J. (2012). "The long-run relationship among regional housing prices: An empirical analysis of the US", *Journal of Regional Analysis and Policy*, 42 (1): 28-35.

[27] Peng, L. and Thibodeau, T. (2017). "Idiosyncratic risk of house prices: Evidence from 26 million home sales", *Real Estate Economics*, 45 (2): 340-375.

[28] Pesaran, B. and Pesaran, M. (2009). *Time Series Econometrics: Using Microfit 5.0.* Oxford University Press, UK.

[29] Scruggs, J. (1998). "Resolving the puzzling intertemporal relation between the market risk premium and conditional market variance: A two factor approach", *Journal of Finance*, 53 (2): 575-603.

[30] Scruggs, J. and Glabadanidis, P. (2003). "Risk premia and the dynamic covariance between stock and bond returns", *Journal of Financial and Quantitative Analysis*, 38 (2): 295- 316.

[31] Tsai, I. C., Chen, M-C. and Ma, T. (2010). "Modelling house price volatility states in the UK by switching ARCH models", *Applied Economics*, 42 (9): 1145-1153.

[32] Veronesi, P. (2000). "How does information quality affect stock returns?", *Journal of Finance*, 55 (2): 807-837.